

IMPACT OF MEANINGFUL USE ON CLINICAL WORKFLOW IN EMERGENCY DEPARTMENTS

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ABSTRACT

Purpose: (1) To investigate empirically the effects of meaningful use (MU) criteria on efficiency and quality metrics regarding clinical workflow at two urban emergency departments (ED) with different Electronic Health Records (EHRs); (2) To develop contextually-plausible and relevant patient safety and quality guidelines for EHR improvements

Scope: Advances in health information technology (HIT), such as EHRs, can reduce the burden on clinicians, potentially improving quality, safety, and efficiency of their care activities. EHR acceptability and impact are of increasing importance. We ask how we can leverage these advances in HIT to increase efficiency (time and cost) without compromising safety.

Method: A mixed-methods approach utilizing semi-structured interviews, ethnographic observations, clinician shadowing, EHR data logs, and sensor-based technology was used for data collection. To generate a composite picture of ED workflow, we used a combination of qualitative and novel data analytic and visualization approaches.

Results: Changes in clinical workflow with EHR implementation are influenced by the nature of clinicians' tasks, as dictated by specific organizational contexts (e.g., whether it is a teaching environment). These changes reflect an intricate relationship between EHR-related clinical activities (e.g., documentation, chart review, medication ordering). We identified generalizable mechanisms for characterizing aspects of workflow, where use of specific modern technology increases efficiency, and suggest ways to manage actions that have more chances of generating errors, affecting the quality of care.

Keywords: Clinical workflow, EHRs, emergency departments, meaning use, clinical performance, data analytics, visualization

PURPOSE

The overall aim of this research is to investigate the effects of meaningful use (MU) criteria on clinical workflow activities in two emergency care settings. The specific aims are:

- **Aim 1:** To investigate patterns of clinicians' use of EHR within the Emergency Department (ED) workflow with specific emphasis on information seeking behaviors, team interactions, and clinical decision-making, while the organization is addressing Stages 1 and 2 of MU criteria requirements
- **Aim 2:** To evaluate the changes in a set of four clinical quality and efficiency metrics both prior to, and post MU implementations for Stages 1 and 2; and trace the potential contribution of the changes in the metrics to the aspects of clinical workflow identified in Aim 1. We specifically examine ED-based MU criteria related to door-to-doctor time, admit decision time, boarding time, and walk out rate.
- **Aim 3:** To develop contextually-plausible and relevant patient safety and quality guidelines for EHR improvement that may be suitable for incorporation into future MU stages

SCOPE OF RESEARCH

Electronic health record (EHR) systems, long touted as a key for supporting efficient and quality-integrated health care, have received increased attention over the last several years [1], both as a result of federal mandates, and as a result of their potential to improve patient safety and efficiency. EHRs support several functionalities including (a) documentation of patient care (b) clinical decision making (c) computerized provider order entry, and (d) communication between care providers. However, the widespread adoption and use of EHRs was relatively slow, partially due to factors such as their usability [2], increased implementation and maintenance costs, limited integration and support for clinical workflow activities, care provider resistance, information privacy and security concerns, and lack of uniform standards. Past research has suggested that the lack of standardization in the use of EHRs has caused unintended negative consequences, leading to adverse events and medical errors. In order to stimulate EHR adoption and standardization of use, the Health Information Technology for Economic and Clinical Health (HITECH) component of the American Recovery and Reinvestment Act (ARRA) of 2009 [3-5] offers healthcare providers financial incentives for the implementation and "meaningful use" of certified EHRs. The Centers for Medicare and Medicaid Services define "meaningful

use” criteria as the use of certified EHR technology to achieve the following objectives: “(a) improve quality, safety, efficiency, and reduce health disparities; (b) engage patients and families in their health care; (c) Improve care coordination; (d) Improve population and public health; (e) all the above while maintaining privacy and security”.

Three interdependent stages along with a set of mandatory criteria have been formulated to help healthcare institutions and practices gradually to achieve MU objectives. In response to HITECH, healthcare practices, including hospitals, outpatient centers and ambulatory care settings, are rapidly implementing EHRs. The adoption of MU criteria objectives is critical because the mere implementation of EHR systems does not guarantee improvement in quality of care [6]. Furthermore, MU incentives have been criticized for their top-down approach built with limited evidence on clinical workflow needs and requirements. While several anecdotal reports exist, only a handful of empirical studies have evaluated the impact of MU criteria Stage 1 implementations and these studies are primarily based on self-reported measures from care providers through surveys and interviews [7].

The focus of our investigations was on the impact of EHRs and MU criteria on ED workflow. EDs represent a prototypical information-intensive and collaborative setting: information is continuously generated, and clinicians are constantly searching for the right information required for performing their tasks. Additionally, the collaborative nature of the environment requires multiple clinical personnel to be involved with the care process. Since the ED is considered a gateway for patient care, the variety of cases seen in most EDs requires that clinicians develop reasoning and decision-making skills for a broad spectrum of conditions [8]. EHRs play an important role in EDs and existing evaluation studies that report on the effects of EHR on ED workflow with respect to quality, efficiency and effectiveness in the context of MU criteria are limited. As a result, there is a growing mandate from the public, payers, hospitals, to measure and improve ED performance.

Although results of studies in the ED may not translate to other clinical settings, our framework provides a reliable mechanism for empirical evaluation on the impact of different EHRs on the clinical workflow in the ED. Additionally, given that the ED is a challenging environment for conducting studies of clinical workflow, our studies provide a benchmark for further extension to other ambulatory care settings.

METHOD

Research Design

The overview of the research design across the three aims is illustrated in Figure 1.

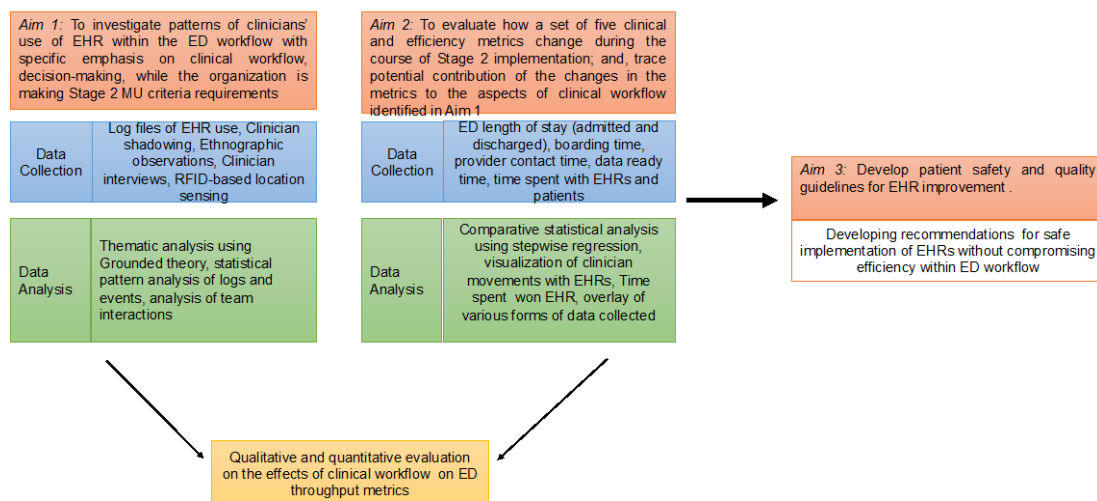


Figure 1: Overview of Research Design by Research Aims

Context and Settings

Studies were conducted at the EDs at two academic medical centers, which had distinct ED staff organizational structure and utilize different EHR systems.

Icahn School of Medicine at Mount Sinai's (ISMMS) ED (Site1) is an urban academic medical center. The adult ED at ISMMS is a 44-bed unit that serves approximately 100,000 patients annually with nearly 27% of these individuals being admitted to the hospital. Approximately 49 attending physicians, 60 residents in ISMMS's 4-year residency, 2 nurse practitioners, 11 physician assistants, 90 nurses, 32 EM technicians and 34 clerical personnel make up ISMMS's ED staff. Attending physicians are located in each area throughout the week, with the exception of Acute 2 which has no attending physician between 1am-7am on weeknights and 11pm-7am on weekends. In general, there are three shifts for attending physicians: 7am-3pm, 3-11pm, 11pm-7am. Residents are placed on a staggering schedule throughout the day while nurse shifts are generally 7am-7pm or 7pm-7am.

In 2015, ISMMS adopted the split flow model to improve the efficiency and effectiveness of patient care in response to the growing boarding crisis. ISMMS uses Epic ASAP 2014; an ED specific interface that coordinates ED visits. In Site 1's acute ED, clinician workstations are grouped together in two large pods with patient beds lining the perimeter of the space. Individuals classified as in need of a bed would be sent to this area while there is a separate room for less severe cases

Mayo Clinic, Phoenix's ED (Site 2) is also part of an urban hospital and includes a 24-bed unit with 9 additional hallway beds. Annually, the ED serves approximately 33,000 patients with 50% of these individuals being admitted to the hospital. To increase efficiency and reduce length of stay in the ED, Mayo Clinic ED utilizes a rotational assignment system to assign patients to physicians and nurses (Traub et al, 2016). This system employs a predetermined algorithmic which assigns patient to physicians or teams rather than relying on physicians or teams to assign themselves to patients. This Clinic's ED uses the Cerner Millennium EHR, and is in the process of transitioning to Epic. Similar to Site 1, physician and nurse workstations are centralized and situated in close proximity, with patient beds lining the ED walls.

Approximately 30 attending physicians, 48 nurses, 16 EM technicians and 6 health unit clients make up Mayo Clinic's ED staff. There are eight predefined physician shifts throughout the day that last 9 hours. Nurses and health unit clients are placed on a staggering 12-hr shift schedule throughout the day: beginning at 7am, 9am, 10am, 11am, 12pm, 3pm, and 7pm.

Describing the roles of two distinct EHRs in clinical workflow provides a foundation for evaluation of system specific and system invariant patterns. Both study sites offered EHR training to clinicians: ISMMS offers an 8-hour training session and Mayo Clinic provides a two-day session, totaling 8 hours.

Participants

Participants included attending physicians, residents and nurses. A total of 50 participants were recruited from each of the two sites. All participants provided written consent prior to participation. A copy of a signed consent form was given to the participant and the original was filed in the PI's office. Given that we used various methods of data collection, sub-sample sample the participants were selected from the recruited pool for each of study method. This was particularly important for studies requiring field data, such as observation, shadowing, and the use of sensor-based technology. The study was approved by the Institutional Review Board (IRB) at NYAM, ISMMS, as well as at the *Mayo clinic*.

For collecting the non-field data (i.e., log files), participants were provided with information about the RFID study and notified about the access to data logs in their consent forms. They were offered a stipend of \$50 for completing all three of these tasks, the RFID tracking, Interview, and Shadowing tasks, and \$35 for completing two, and \$20 for completing just one. All participants were assured of privacy and security of the collected data. Patients were exempt from the various studies.

Data with any identifying information about participants were removed, and only numeric subject identification codes were used for analysis. A master list was retained in the PI's office that linked participants to their codes. The data were stored on encrypted computers and were accessed only on computers within the respective hospital's internal network. The collaborative relationship between the Mayo-Clinic, Phoenix, and the Department of Biomedical Informatics (BMI) at Arizona State University, allowed our investigations to access this data through BMI, where secure Mayo Clinic network could be used. Similarly, a collaborative relationship between ISMMS and the NYAM allowed us to access the ISMMS data through a secure server at

NYAM. Only the investigators listed on this project had access to the data.

Data Collection

Given the very close relationship between data collection and analysis to build workflow models, some of our analyses are described in the context of data collection. To address Aim 1 and to establish a baseline understanding of clinical activities, information seeking, and workflow at both study sites, we conducted ethnographic observations and clinician shadowing, semi-structured interviews, and used sensor-based clinician tracking methods for data collection.

Semi-structured Interviews

The goal of interviews was to examine the perceived nature of changes in the clinical workflow as a result of EHR use and MU criteria compliance, and any differential effect of EHR use on clinical workflow (at each study site). Development of semi-structured interview questions related to EHR use, MU and workflow were based on discussion with experts and consultants at New York-Presbyterian (NYP) and ISMMS hospitals. A framework for interview analysis was created to generate interview questions related to: EHR implementation and use, knowledge of MU and MU criteria compliance, and the impact of EHR on the quality and safety of patient care. Inter-rater Reliability: After transcription, two researchers, one each from ISMMS and Mayo Clinic, coded responses based on common themes. The coding reliability across the three coders was 0.84, showing a relatively high degree of agreement. All coding disagreements were then discussed and resolved to generate a more standardized coding scheme, leading to a better reliability index of .98.

Ethnographic observations and Clinician Shadowing

Ethnographic observations were used to develop an understanding of the overall characteristics of clinical work practices at each clinical site. These data can also inform us about multitasking, interpretation, and other elements that would create high clinical load on clinicians. The common factors between the two sites helps in generating a generic nature of the clinical workflow. Observers at each site received training with our team in real clinical observations and worked closely with a clinical study coordinator. Observations were conducted in all ED areas with EHRs, patient examination rooms, corridors with patient beds and nursing stations. Observations of ED rounds and clinical activities that characterized patient care in the ED were recorded at different times of the day during 21 sessions. Observations lasted approximately 170 minutes. Researchers focused on clinicians' use of EHR, team interactions, and clinical activities in the ED

Clinical Shadowing is a commonly used behavioral observation of a user in their natural environment that provides useful real-time information about what people do, and when they do it in the context of other related activities and interactions. At Mayo Clinic five attending physicians and five nurses were shadowed during their shifts and at ISMMS, nine attendings/residents and two nurses were shadowed. After the initial data collection, we conducted brainstorming sessions to reflect on the observation process and the data collection procedures to resolve any issues generated during the observation and shadowing. Data collection and coding were done independently at two sites. Major disagreements were resolved through discussions with the PI and clinical experts; and a field note template to standardize shadowing data was developed, encompassing time, location and clinical activity observed. This template together with ethnographic notes was employed at both sites.

EHR Data logs

Audit trail data logs of clinician interactions with the EHRs are routinely captured as part of the hospital records. These log files are based on the EHR activities of the physicians during the clinical workflow. They include: physician ID, time stamp of activity, and system interface accessed. In order to comply with the IRB requirements, all identifying information (physician or patient ID) were deidentified for further analysis.

Given the granular nature of these activities, we categorized the identified EHR log-based activities at ISMMS was categorized into 4 generic higher-level categories: documentation, orders, review, and on-screen navigation. *Documentation* encompasses clinical activities such as writing clinical notes during or after a patient encounter. Attestation of resident or physician assistants by attending physicians were also included in this category. *Navigation* describes the usage of search functions as well the transition between various

screens within the EHR system (e.g., exiting orders). *Review* functions include viewing charts, results, previous encounters or vitals via the flow sheet. *Order* category encompasses submitting and accessing orders within the system.

Sensor-Based Clinician tracking (RFID)

Team interactions and activities using Radio Frequency Identification (RFID): The use of RFID-based technologies is motivated by the fact that the use of non-obtrusive sensor-based technology provides a flexible and viable mechanism for capturing interactions among clinicians (attending physicians, nurses and residents). In our research we incorporated and evaluated how RFID technology is used to characterize the team activities in a complex critical care setting by using proxies such as locational proxies gathered by automated data collection techniques.

RFID Sensors (ISMMS): After evaluating multiple options for active RFID sensors, we decided to use a 2.45 GHz gain adjustable RFID reader and tags (manufactured by GAO RFID Inc.). These reader-tag combinations were first pilot tested in a lab environment for accuracy of recording. After this preliminary testing of the tag-reader combination we had to customize a software product that would convert the signals that were received from the readers into time-stamped location identifiers

One of the primary challenges for effectively using RFID for longitudinal evaluation studies is to create a framework for data collection and storage. The data generated by the RFID tracking is voluminous – for each tag, data is recorded approximately in 3-second intervals. This requires efficient and continuous storage. For our purposes we have created a version of a data capture tool that abstracts data from each of the tags, and transforms them into a serially time stamped data stream. The set of the RFID reader–tag combination was in the following manner. First, RFID readers were assigned fixed IP addresses within a network. Second, the RFID readers were programmed to “identify” the tags from different distances (also known as “setting the gain” of the devices). When a tag is within the proximity of the reader (within the set gain of the reader), the signal (along with a time stamp) is transmitted from the reader (via the network) to the software application. This process is applicable to any tag that is within the gain distance of the reader. The conceptual framework of the data transmission through the RFID network is shown in Figure 2.

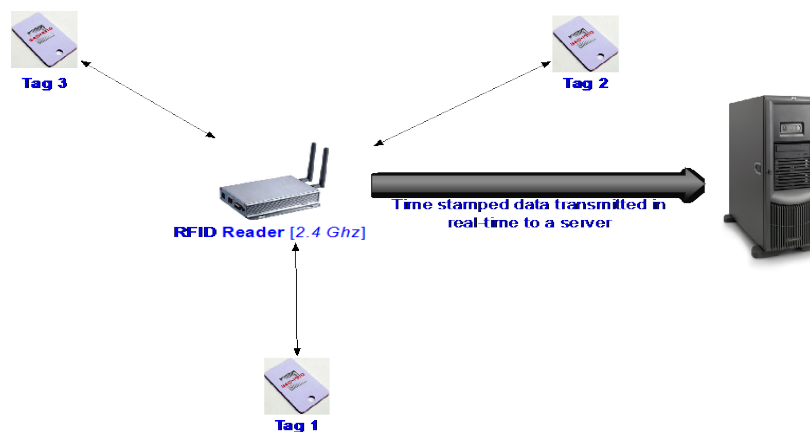
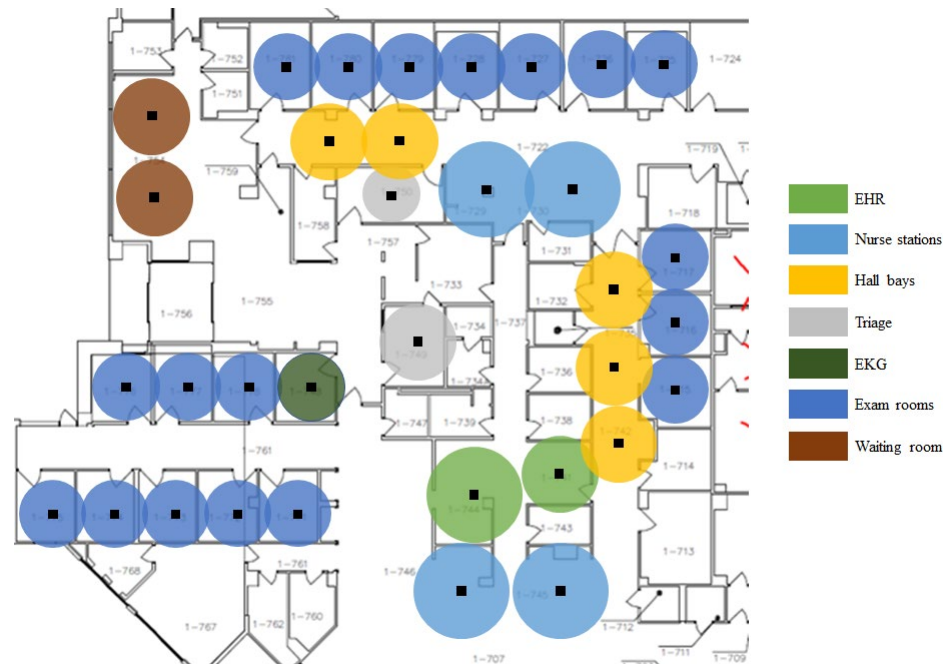


Figure 2. Tag-reader connections and data storage framework

After the initial testing in the lab, we installed the RFID readers at the ISMMS Emergency Department. The readers were positioned at two key locations: two sets of computer stations where physicians and nurses most of their EHR related activities and tasks. Based on the pilot data, we found an interesting (though expected) insight: given the significant number of people who use the area, there was likely to be significant signal absorption (leading to potential loss in location identification). As a result, the gain settings of the readers were constantly monitored to ensure that the readers were recording appropriate signals. During our data collection phase, we tracked the volume of traffic in the reader-installed areas such that signals are not lost during intense traffic periods.

At Mayo Clinic ED, to explore an alternate method of positional tracking using Bluetooth low-energy beacons, we employed the Estimote Bluetooth beacons and Raspberry Pi receivers. Bluetooth beacons and

receivers also afforded a more flexible solution to positional tracking owing to the ability to offload a lot of the computation (for e.g. noise filtering) onto the receivers themselves as opposed to needing to send data onto a server for processing. Bluetooth provides a cost efficient and low-powered alternative for positional tracking with an enhanced detection range. However, some hospitals felt that this method captured large ED range, where some unintended activities outside our investigations may be captured. After the tracking system change, we leveraged the data collected by the proprietary RFID system. The system consisted of ceiling-mounted receivers and an RFID tags carried by tracked clinicians. Figure 3 gives a schematic map of the ED, along with areas of interest (highlighted areas), tracked by the system. There were 59 unique tracked locations including each patient room, hallway bed, workstation areas, nurse stations, and medical supply rooms.



rates of interruptions and multitasking. A general workflow model for each site was constructed, capturing the task order as well as the location in which these tasks were performed.

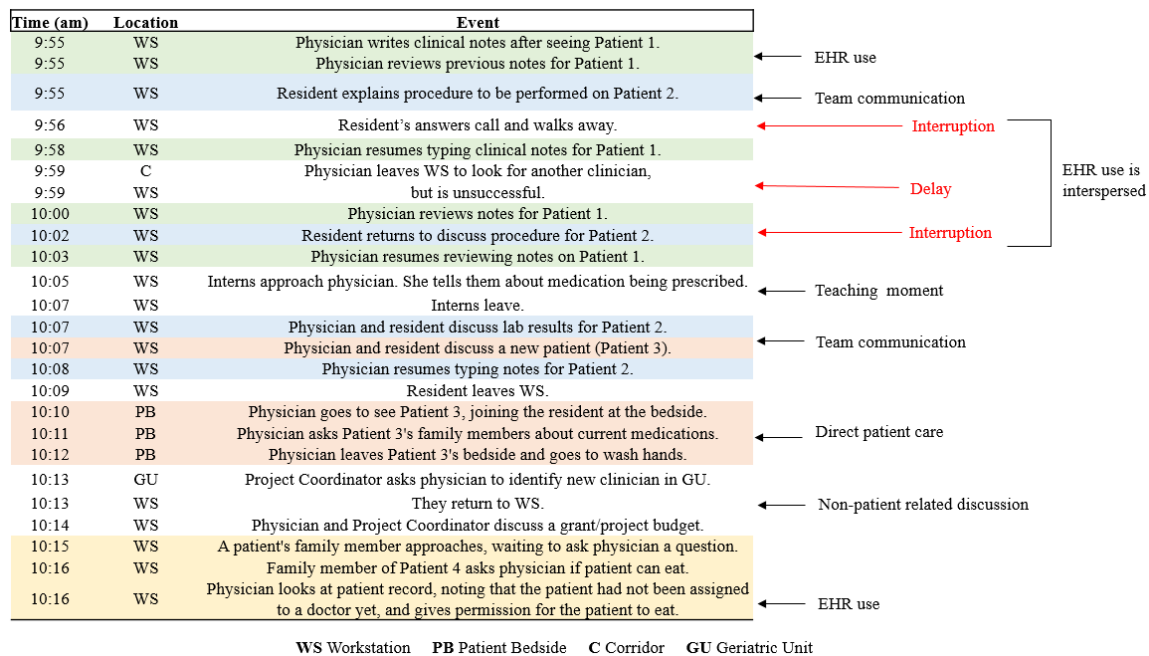


Figure 4. Snapshot with illustrative example of 20 minutes of physician #5 workflow at Site 1 (9:55-10:16am)

In order to create a data visualization for this workflow, we used analysis of Timeline Belt by Zheng et al. [10], illustrating the order in which different tasks were sequentially carried out in the clinic. Each physician observation was symbolized as a row (or a belt) that depicted specific clinical tasks and where any instances of interruptions or multitasking occurred. Clinical and administrative tasks were categorized into three and physical movements were depicted as 'in transit,' any social interactions as 'social,' and any administrative tasks as 'administrative.' The left-hand sides of the bars were aligned with the starting point of the observation sessions with each colored section's length proportional to the amount of time spent on that task or activity. Due to the variations in length of our observation sessions, we represented the activities during the first 170 minutes of observation, our average session length.

Figure 5 depicts the frequency of task transitions for physicians as they completed their clinical activities. Instances of interruption were seen distributed throughout the workflow, whereas multitasking tended to occur in the beginning and about two-thirds of the way through shadowing session. Here, the physician #5's work model begins at 10:00am, reviewing Patient 1's information in the EHR. When the resident returned to the workstation at 10:02am, the physician stopped their review to briefly discuss Patient 2's procedure. After this interruption, this physician returns to their original task of reviewing Patient 1's record. Since Site 1 is a teaching hospital, the physician was observed creating opportunities for "teaching moments" with residents and interns. A possible delay in care was also observed where the physician could not locate another physician, a colleague for consultation, preventing physician #5 from moving forward with the current tasks.

RFID Data analysis at Mayo Clinic: Monte Carlo Simulations

We conducted Monte-Carlo simulations that used transition probabilities to model clinical behavior by simulating thousands of potential runs (i.e., movement from any ED starting location to an end location) and determine the average "cost" of each run. The cost in this case is the time taken to arrive at the end location from any starting location. The determination of appropriate starting and ending locations helped us make valuable and varied judgments on behavior. As an example, we can consider the case of a physician looking up patient data in the EHR workspace and conducting the patient exam. Sometimes a physician may move directly to a patient room and others they may move to other locations such as the nurse station or other exam

rooms first. Determination of the average time taken to move between these locations can help assess time to patient visit for physicians. (Vankipuram et al 2018)

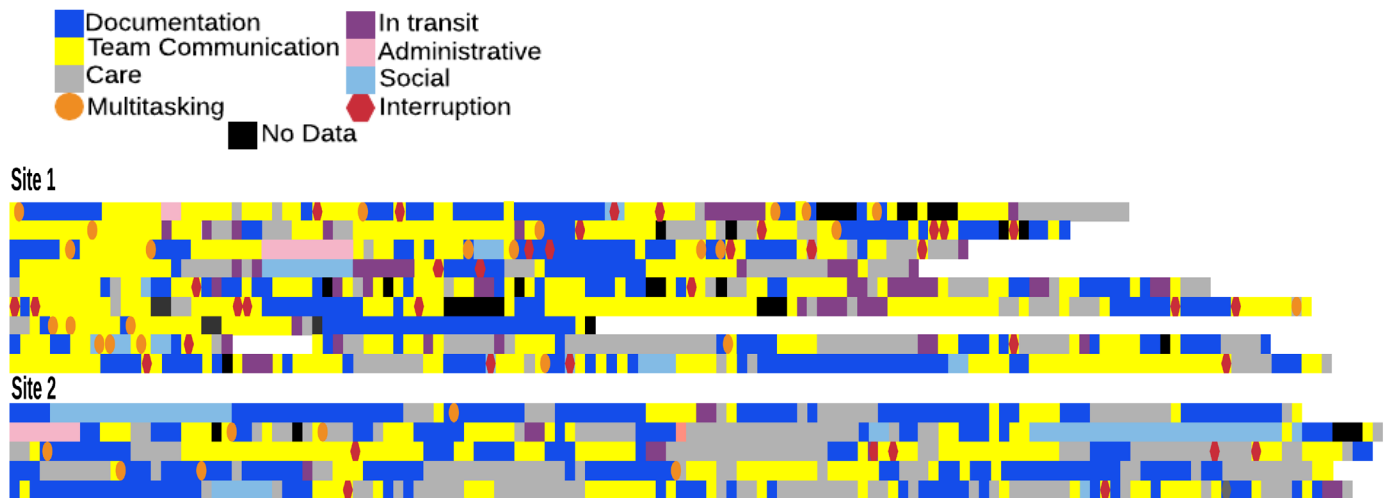


Figure 5. Physician Time Distribution by Clinical Activity at ISMMS (Site 1)

Framework for analysis and Visualization of Clinical Workflow

We created a framework that combines statistical and computational techniques used for sequence analysis to create a set of methods to develop quantitative metrics associated with clinical workflow as well as a set of interactive visualizations to convey feedback (summarizing the developed metrics) to the clinicians. Figure 6 depicts the framework used to develop these visualizations (Vankipuram et al, 2017). The framework is divided into three phases: transformation, analysis, and visualization. The transformation phase largely pertains to computational techniques used to convert raw location tracking data in the form of locations and times to a structure that can then be fed into each analysis module to produce metrics and higher-order results. Finally, the data outputs of the analysis phase were used to generate visualizations. The three phases of the framework were: (i) Transformation: Computational techniques that convert tracking data to alternate representations and structures that facilitate the analysis phase. (ii) Analysis: The utilization of the transformed data in the transformation phase to generate quantifiable measures of workflow used in an assessment or exploratory capacity. (iii) Visualization: Deals with the presentation of results of the analysis phase. Once again these can be used for reporting or to explore elements of workflow.

As an example of analysis that can be conducted using this framework, we charted the probability of immediate movement i.e. without a duration threshold (figure 7). The 'Workspace' and 'Nurse station' notations were chosen to demonstrate the charting of next location probabilities since they are the two locations where the most amount of time is spent. Several of the ancillary locations were combined into a single location 'Other' for simplicity of plotting. Also combined were the exam rooms into one location 'Exam' and the two 'Nurse stations'. The workstation area and nurse stations form a tight coupling, i.e. most likely movement for clinicians seems to be back and forth between these two locations. Depending on the relative positions of these locations, this may or may not represent an efficient use of time. It would be worth identifying the types of information needs for the clinician that are not satisfied by EHR based communication requiring that coupling to exist (Vankipuram et al. 2018).

Overlaying Data from Multiple Sources

Given the goal to model workflow using location information, we extracted relevant metrics to be used in conjunction with EHR log data. Physician location tracking data was mapped onto their EHR use to provide context and to gain insight into what they actually were doing while at the workstation.

At ISMMS, we first used EHR log files to characterize the nature of activities on the EHR during clinical workflow, conducted over a two-month period, involving over 2000 patients based on access to clinical information, the time spent on accessing such information, and its potential impact on efficiency metrics. At the

same time, we used RFID technology to capture the location-based data on attending physicians, residents, and nurses. Over 3-month period, overlapping RFID and EHR log data for 2324 patient encounters over 15 sessions were collected, lasting approximately 4 hours (mean=3.6 hours) each.

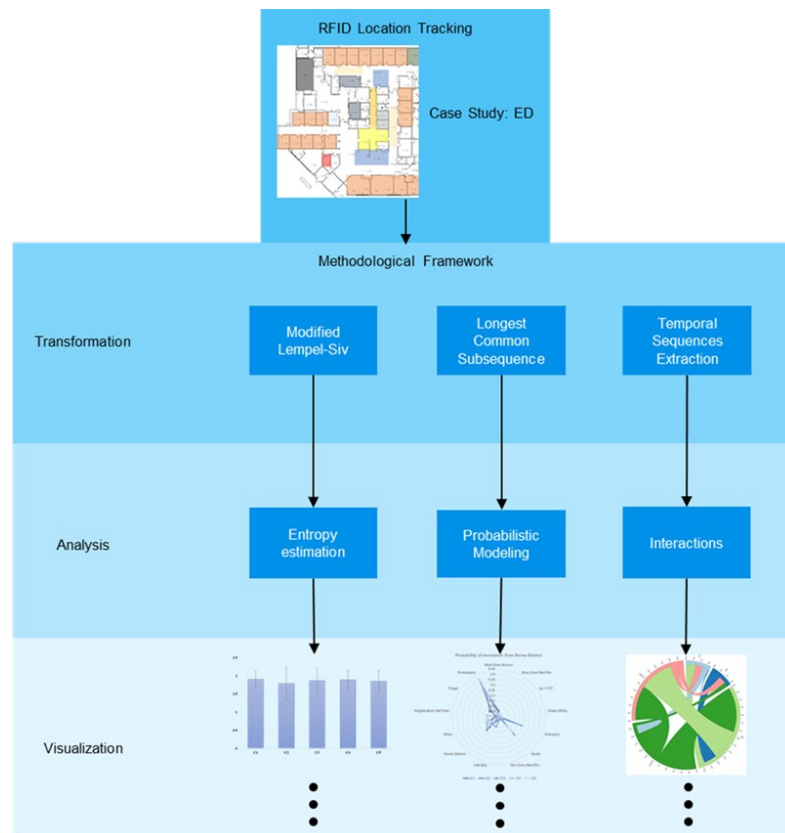


Figure 6. Framework for Clinical Workflow Analysis and Visualization

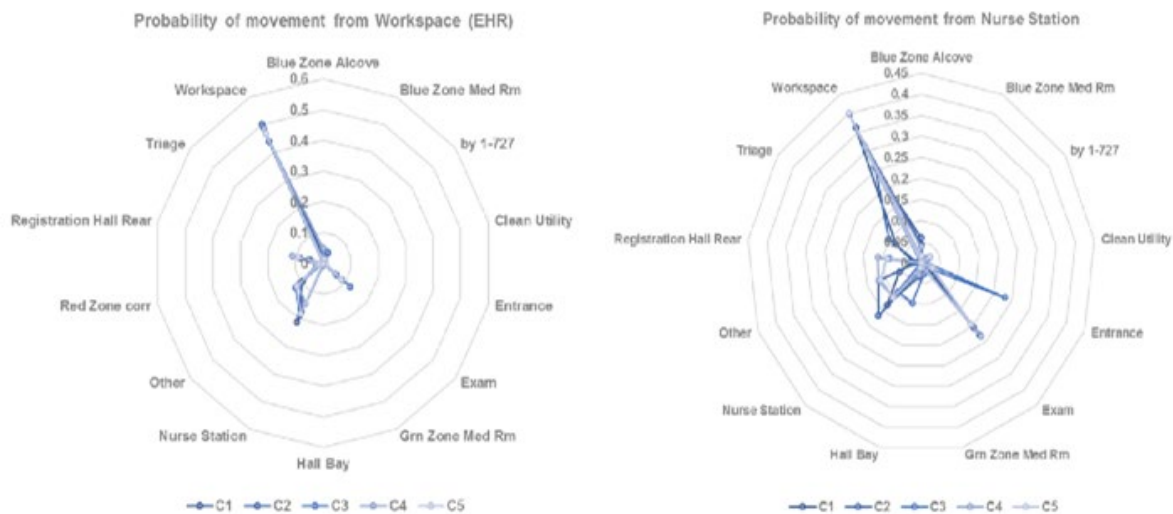


Figure 7: Probability of physician movement from workspace to locations in the ED

First, we characterized EHR and non-EHR allocations of time during workflow; and then, ascertained the different EHR-based activities that were performed by the clinicians. Towards this end, we performed the

following transformations to match and evaluate the data: RFID data for each clinician, per session, was separated into a binary function of whether the clinician was present at one of two locations or not (i.e., performing documentation or involved in patient care activities). Given that these locations represent the “documentation centers,” with several available workstations, our assumption was that most, if not all documentation activities occurred here.. It was assumed that if the clinician was not present, then he/she was involved in some direct patient care activity (present/absent at the workstation location).

At Mayo Clinic, workflow was categorized into three categories using RFID location tracking and EHR use: perceived, real, and ideal. The goal of this work was to derive an understanding of real workflow from the data sources mentioned and combine them with a notion of workflow perception, generated from coded interview data (Denton, C.A., Soni, H.C et al. 2018) to suggest improvements in workflow or support that could be provided to reach a more idealized state. The RFID data were used to map two measures (multi-patient visits and information transfer) that are potentially affected by EHR usage (or perceptions of EHR usage). RFID data captured movements of physicians and were contextualized with observational data. We found two aspects of physician movements to have the greatest potential impact on their perception of EHR use: (i) multi-patient visits and (ii) information transfer during clinical workflow.

As an example of the type of findings derivable using this data Figure 8 shows the probability distribution of multi-patient visits. We speculated that multi-patient visits are related to an increase in cognitive burden in environments (such as the one being considered) where there is no EHR use within patient rooms. So, in this case, the physicians had to place the information of the patient in working memory. Physicians 3 and 4 showed elevated levels of this behavior compared to the others while having a neutral to negative view of the EHR as found in interviews. We could speculate that the multi-patient visit behavior is related to a less positive perception. To achieve a more ideal state from perceived and real state of workflow, moving physicians 3 and 4 towards the less physically efficient (more cognitively efficient) approach may help increase their overall satisfaction with the EHR.

We also computed the correlation coefficient (Pearson) and statistical significance of each attribute in the EHR usage data (from the data logs) and the multi-patient visits per day for each physician and all physicians (by computing the mean of all their EHR usage values). A heatmap was created of the highest positive and negative correlations at the 95% confidence level ($p \leq 0.05$) across all physicians. In our data, two physicians showed an elevated number of multi-patient visits, and they had different EHR usage elements that correlated with it. The reason for computing correlations individually and as a group was that the former could be used to target specific areas of the EHR that could impact broader workflow and the latter could be used to find common themes in the group that may require different types of support/interventions.

An interesting finding was that use of review MPages (which is specific chart review feature of the EHR) was correlated with a reduction in multi-patient visit behavior for physician. However, MPages or EHR pages are not used by all physicians. If utilization of this feature could help reduce instances of multi-patient visit behavior, then specific training could be enacted on this feature for the group.

Measures

Overall, MU measures which reflect, efficiency, quality and safety of patient care with EHR implementation and use were considered in our research, but they varied on how these measures are considered, depending on the methods we used. For *efficiency metrics*, four ED MU measures were used, these include

Door to diagnostic evaluation: Median time from patient's first entry into the ED to being seen by a physician, admit decision time: Median time from patient's first entry to the decision to admit from the ED, Boarding time: Median time for patient's arrival in the ED to their departure after being admitted, and Walk out rate: Patients who leave ED without being seen (see Figure 9 for a summary description of the measures).

For *effectiveness metrics*, we used a number of measures, capturing clinical workflow. These include:

- a) Time distribution and effectiveness of clinical practice: Time spent on patient related activities and on various specific components of EHRs during clinical practice. These include Documentation, Navigation Patient Chart Review and Medication Order, for example, time it takes to navigate through the ER to completed the task, and in doing so, what and how any safety factors are compromised.

- b) Time distribution for efficient practice: Movement of clinicians with respect to EHRs and pattern of staff organization, including visits to nurse stations, staff rounds
- c) Measure of cognitive load in practice: Number and types of clinician interruptions and multitasking during practice, affecting work efficiency and potentially, safety
- d) Pattern of movement during information transfer (efficiency/effectiveness of information exchange), and
- e) Pattern of patient visits during patient-doctor encounter (single or multiple) and its relationship to documentation, review etc. on workstations (Efficiency and effectiveness)

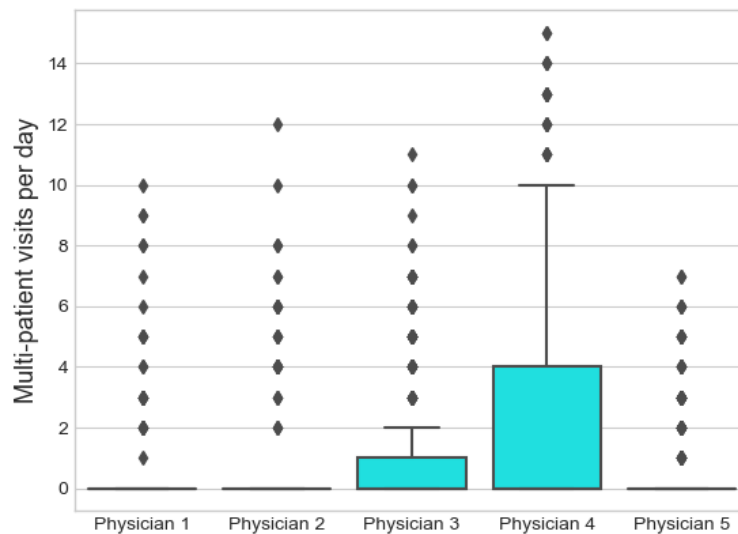


Figure 8: Probability distribution of number of multi-patient visits (defined as visiting multiple patients between each EHR session) per day for each physician. The diamonds represent the total number of multi-patient visits on outlier days for each physician.

RESULTS

1. Ethnographic observations and clinician shadowing to develop an understanding of the overall characteristics of clinical work practices at each clinical site

At ISMMS, physicians spent approximately 61.3% of their time in their workstation area, with 25% of this time spent on the EHR. Physicians spent most time performing documentation tasks, where worked closely with physicians in task sharing to process patient information. At the workstation, physicians were engaged most in team communication, including information handoffs and consultation activities. Frequent task transitions and interruptions in clinical activities were observed at this site.

At Mayo Clinic, physicians spent about 51.7% of their time at their workstation, with 31.4% of this time dedicated to EHR activities. A majority of this EHR-based time was dedicated to the review of patient records. Documentation time was less than what was found at site 1, and medical scribes were used for transcriptions of dictated clinical notes. Additionally, these physicians overall spent more time on direct and indirect patient care than on the workstations (See Figure 10).

2. The frequency of task transitions was seen in the visualization form of the temporal order of clinical events with more transitions at site 1, including multitasking, occurring primarily earlier in their shifts. Instances of interruption were distributed throughout the session. Team communication occurred before and after other clinical activities, and frequently occurred in combination with EHR documentation. Fewer transitions between tasks were observed at site 2. EHR use was frequently followed by patient care and then brief team communication. Overall, few interruptions were observed here. This is seen in Figure 5.

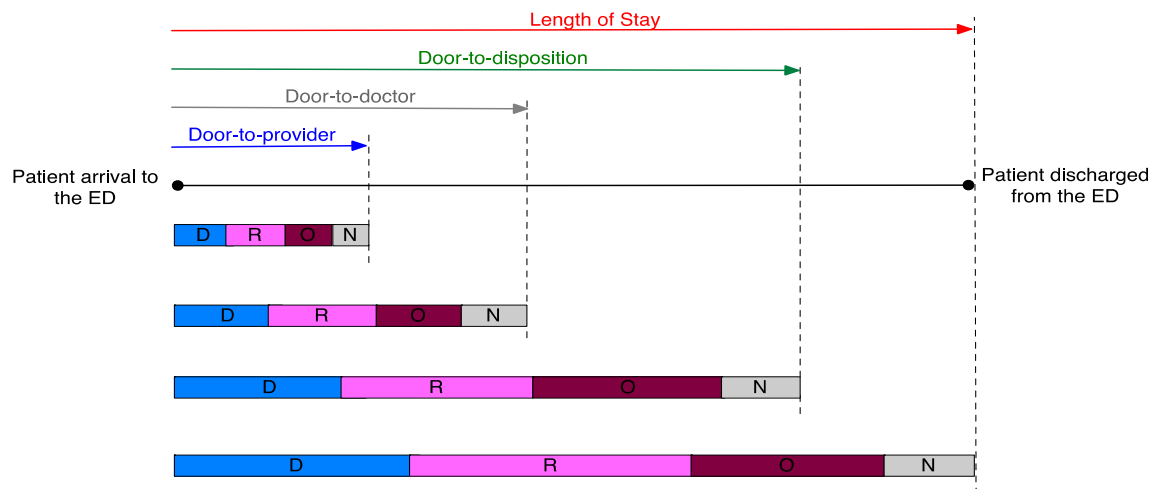


Figure 9. Patient trajectory from arrival to the ED to discharge. The four ED performance metrics: door-to-provider, door-to-doctor, door-to-disposition, and length of stay are shown with respect to a patient's care trajectory through the ED. On the lower half, the time spent on each of the four EHR-based activities during each of the performance metric measurement phases is shown: documentation (D), review (R), orders (O), and navigation (N). The time spent measures are not drawn to scale.

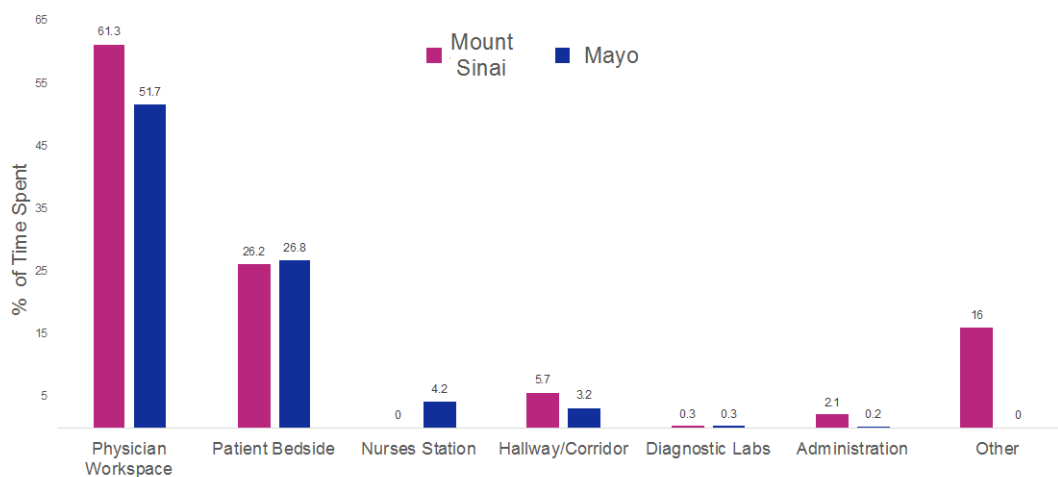


Figure 10: Time spent on clinical activities by location at two sites

3. Clinician perception of time spent with patients

The majority of the physicians reported changes in their clinical activities as a result of EHR use, with most reporting a negative effect on their time spent with patients (less time: 50%, Site 1; 89%, Site 2), and having a neutral-to-positive influence on their performance with four MU metrics, with decrease in both door-to-doctor time and in admit decision time at Site 1. EHR use was also believed to influence the efficiency of physicians, quality of care they provided, and overall patient safety, given in Figure 12.

A number of EHR usability concerns reported, and the most prominent concern was the “number of clicks” required to complete tasks (51%), which is consistent with previous research. Other usability concerns included navigation (18%), access to information (8%), repetition of tasks (8%), screen clutter (8%), and multiple windows (6%). With these usability concerns in mind, physicians reported on a 10-point scale that their EHRs supported patient safety (9), followed by quality of care (7.3), and finally, efficiency of task completion (6.7).

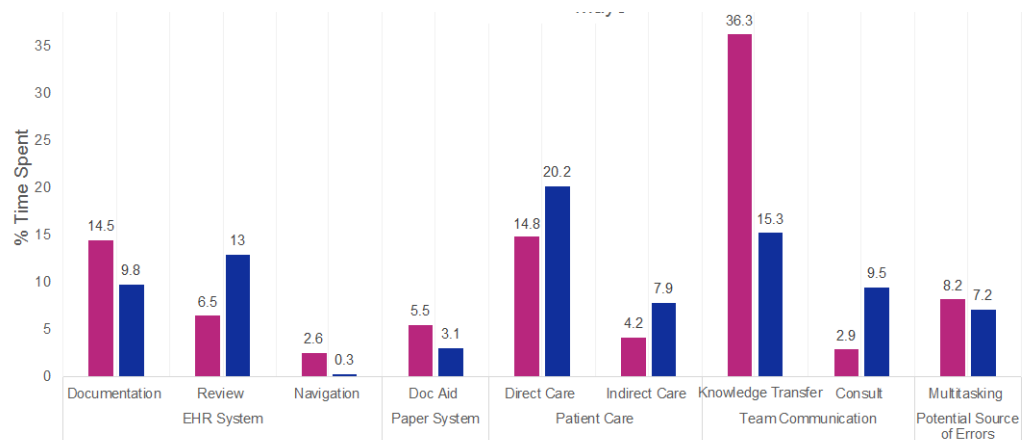


Figure 11: Time spent on clinical activities by task at the two sites

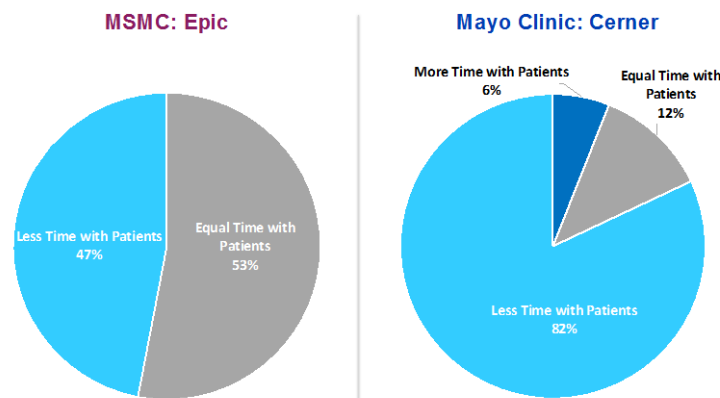


Figure 12. Interviews – Impact of EHR: Perceptions of Time Spent with Patients

4. Use of sensor-based technology (Bluetooth beacons) at Mayo Clinic show that one of the MU criteria (door to doctor time), when automated is similar to or better than the hand-written time, as shown in Figure 13.
5. Mapping EHR data logs and RFID (combined)

At ISMMS, Physician EHR use was mapped onto their location tracking data. Data logs show Physicians split their time almost equally being at the computer and with patients (nearly 50% each). Across two observed locations, the primary activity for physicians was documentation (58%) followed by review (24%), orders (15%), and navigation (3%). In contrast, nurses spent more time away from the computer (70%), being potentially involved in patient care related activities and tasks. For nurses, the activities included documentation (69%), review (12%), orders (13%), and navigation (6%).

6. Prediction of clinician movements via visualization using RFID

With the use of specific EHR features, we were able to predict whether a physician would visit multiple patients in-between EHR visits. These features were related to time spent on reviewing charts, orders, electronic documentation, and transcription. Transcription was correlated with a reduction in multiple patient visits as it may take a long time to dictate notes. Chart review and orders were also related to nurse station visits. Prediction of physician behavior showed a pattern where the strongest location-based relationships were found between the workspace, hallway, exam room, nurse's station, and the rear

registration hall. Physicians were far more likely to move to the workspace from exam rooms and nurse stations.

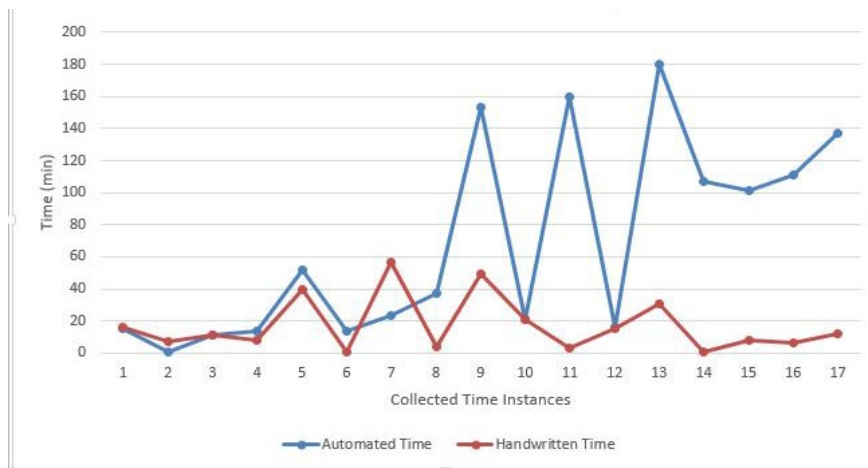


Figure 13. Automated and Handwritten Time Comparison for “Door to Doctor” Time

CONCLUSIONS AND DISCUSSION

Differences in Clinical Environments

Like most academic environments, clinical workflow at the ISMMS was characterized by team communication, where patient cases were discussed with residents and students and the communications were documented in the EHR. This communication also involved resident and student teaching at the work station. Parallel processing of multiple patients’ data occurred with multitasking and interruptions interspersed between clinical activities, as in most complex settings. The resulting fragmentation of workflow was offset by the distribution and transfer of knowledge during times of team communication as a shared knowledge base that was created between attending physicians, residents, and nurses. Team communication also allowed for any error checks, making sure safety was not compromised. In addition, the team also created a learning environment for future clinicians. It may not be most efficient, but our data showed that using sensor-based technology, several of the work processes can be automated and dashboard support can offload some of the organizational task

In a less-academic environment, such as the Mayo Clinic, most attending physicians processed their patient information (except for documentation) by themselves, working individually, rather than relying on team members. In this setting, a unique mechanism of assigning patients to physicians is employed to ensure that the work is completed efficiently. Physicians in this ER setting saw one or two patients at a time and completed as much of the documentation about one patient before moving to another, in a linear manner. This serial processing limits the need for multitasking and the prevalence of interruptions. There is less chance of an error being caught, given that there are no team safety checks, which may compromise safety. Mayo Clinic has requirements for following a relatively rigid but a firm protocol, which ensures some safety checks. Implementation of specific safety checks is advisable at other similar sites.

Time on EHR Tasks

At site 2 (Mayo Clinic), automated location tracking in context (shadowing) showed that time spent at physician workstation was on chart review, since data documentation was done via scribes. This was also a way to offload some of the clinicians’ tasks, thus reducing the time (and cost). This was shown to be consistent with shadowing results, where our measure using RFID was relatively close to reality. With the use of specific EHR features, we were able to predict multiple patient visits in-between EHR documentation. This adds to the physicians’ cognitive load and can be reduced with adequate intervention.

The strongest location-based relationships were found with physicians where they were more likely to move to the workspace from exam rooms and nurse stations. There appeared to be an information need requiring multiple moves to the nurse station in-between patient visits. A framework was developed combining statistical and computational techniques used for sequence analysis to predict physician behaviors and create a set of methods to develop quantitative metrics associated with clinical workflow as well as a set of interactive visualizations to convey feedback (summary of developed metrics) to the clinicians. This could be invaluable support tool in clinical practice. The derived measures via visualization of clinical workflow using sensor-based technology, can support researchers and clinical stakeholders, as they identify bottlenecks in the workflow process, which can be further investigated in greater detail using other complementary techniques such as, ethnography.

EHR Use and Clinical Performance

At ISMMS, data showed positive correlations between physician review of patient charts, and door-to-disposition time and with length of stay (LOS). Physician patterns of EHR use and direct patient care were consistent with shadowing sessions, showing some relationship of log data to clinical activity. However, RFID findings were inconsistent with shadowing sessions, suggesting individual differences in care are greater at this site than at the Site 2. EHR data also show increased time spent on documentation and chart review among physicians, which shows the need for their reliance on long-form documentation in order to manage and situate their activities.

This can partially be attributed to the workflow in academic medical centers. In other words, academic medical centers have a multi-layered process of iterative review with residents performing frontline clinical activity, supervised and guided by attending physicians. The downside, as highlighted from our results, is the potential impairment in performance (in terms of longer time involved in the care process).

In addition, the results also highlight the team-based care in complex distributed settings such as the ED, where multiple clinicians (including residents, nurses, pharmacists and attending physicians) are involved in the care process. The data generated during this care process show a non-linear fashion of data update. As a result, decisions are often delayed till there is appropriate updating of data. Multi-layered process of review may help improve patient safety (confirmed by shadowing sessions), and technological support (such as RFID) can be sort to offload some tasks, and scribes can be assigned for documentation task.

Use of Automated Technology to Off-load Clinician Tasks

Use of sensor-based technology at Mayo Clinic show that of the MU criteria, door to doctor time, could be automated with more accuracy, freeing doctors from extra task and cognitive load, and thereby contributing to reduction of ED overcrowding (increasing patient safety). However, during observations and sensor analysis, we found that this measurement was not precise, with significant variations in the time when the doctor sees the patient with respect to when the tagging records begins. The nature of workflow in the ED appear to be responsible for this variation. Similarly, decision time is also imprecise, given that the time when decision is made is not the same time when the physician enters in the computer. A more precise measurement scale needs to be developed.

OUTCOMES [MILESTONES]

1. *Perceived Influence of EHR on Clinical Workflow and Performance Metrics* as a result of EHR use and MU criteria compliance, at two clinical sites.
Manuscript based on analysis of semi-structured interviews at both clinical sites on clinical workflow and Meaningful Use (MU) performance metrics was published in *Applied Clinical Informatics* journal (Denton, Soni, et al, 2018) and a poster at AMIA Conference Proceedings (Denton et al 2016).
2. *Shadowing data analysis to characterize two clinical workflows to understand the work process, including, interactions, interruptions, etc. within the complex organizational structure of individual environment.* With integration of data from two study sites, we characterized two distinct workflow models that provide an integrative framework for interpreting our data, including those from RFID location tracking, EHR data logs,

shadowing, and clinician interviews. A manuscript is being prepared for submission. A poster was also presented at the meeting of AMIA *Clinical Informatics* Conference (Soni, et al 2018).

3. *Demonstrating clinical relevance of developed visualizations for clinicians*
We developed a web-based dashboard representing workflow metrics from RFID and EHR summary data for presenting derived metrics to clinical and administrative end users. Our goal is to provide value from the tracked data for clinicians who do not have ways of assessing and modifying their own behavior based on tracked data. It is also potentially useful for process analysis and behavior modifications based on technological changes or by discovering existing bottlenecks. Manuscripts were published in JBI (Frisby, et al 2017, Vankipuram et al, 2018) and in AMIA Conference Proceedings (Vankipuram, et al 2017)
4. *Analyzing EHRs log files for tracking clinical workflow at ISMMS to characterize the relationship between pattern of EHR use and performance.* Evaluation of the role of various EHR-based activities on the overall performance metrics in the ED resulted in a manuscript published in ACI (Kannampallil, et al 2018)
5. *Extrapolating qualitative workflow metrics from clinician location tracking data.* A manuscript published in the JBI (Vankipuram, et al, 2018) and a book chapter (Vankipuram and Patel, 2019).
6. *Simulation of clinical behaviors, specifically time spent at various locations and their impact on time to see patients to capture more precisely the impact of EHRs on performance.* Leveraging the transition probabilities of physician movements using RFID data to develop Monte-Carlo simulations to determine with a greater level of statistical certainty the time spent in locations or tasks prior to a patient examination in the ED workflow. Given the computation of transition probabilities, Monte Carlo simulations help in ascertaining time spent during a workflow process. Simulating a set of physician movements using transition probabilities is functionally equivalent to observing the behavior. As the transition probabilities are computed from a nearly year-long dataset, these patterns are likely to be consistent. This means that we can discover time taken or number of transitions made to reach some end location of interest (e.g., an exam room) to compute EHR to patient visit time. (Vankipuram and Patel, 2019)
7. *Combining multiple data sources.* Overlaying RFID, Shadowing and EHR log files from Mayo Clinic to develop a more comprehensive picture of clinical workflow, characterizing a fine-grained relationship between EHR work pattern and other performance measures. Overlaying location tracking RFID data on the physician shadowing data and EHR log files data provided us with a deeper insight into clinical flow and the impact of EHRs on the clinical activities. Time consuming human intensive analysis can be replaced by the use of technology. A manuscript was accepted for publication in JBI (Vankipuram et al 2018).
8. *Combining RFID and EHR log files from ISMMS to characterize the interaction pattern of nurses and physicians with components of EHR.* Combined 15 sessions of RFID and log files, we performed a combined analysis to evaluate the process by which clinicians split their time between patient care and EHR-based documentation activities A manuscript is under review. (Kannampallil et al, 2019)
9. Development of guidelines and recommendations. A set of preliminary recommendation guidelines based on findings from all studies are given below.

SIGNIFICANCE AND RECOMMENDATION GUIDELINES FROM FINDINGS

The primary purpose of this research program is to understand and improve clinical workflow—both from EHR-based perspective, and from a workflow perspective—in order to improve efficiency, quality, and safety. This will require the translation of easily available secondary data (e.g., EHR data logs, sensor-based data) into pragmatic information that can be used by clinicians during their clinical activities, and displayed through dashboard visualizations. Our findings regarding usability also highlight the need for on-going interface improvements; this primarily arises because new features and tools are constantly added on the EHR, increasing the learning curve for users, and potentially contributing to usability challenges. We used MU criteria as an external metric for evaluating clinical workflow. However, with changing perspectives on MU use and its role, new measures should be considered.

EHRs often act as an external decision support system (offloading extra cognitive load), as long as we are clear about what purpose they serve in various environments. EHRs support different activities in academic and non-academic environments, making it important not to evaluate and judge all EHRs on the same scale. Performance and efficiency are important, but they are not the only consideration. Academic medical centers have multiple functions including training, education, and collaboration; this improves the quality and safety of care. By managing complexity (not reducing it) through cognitive and technology support, we support both

learning and safety as well as improve resilience in the environment.

How can we leverage technology in the ED to increase efficiency without compromising safety (within a given margin of error)? Our findings suggest:

- Using automation such as tracking devices can increase efficiency without compromising safety
- Having scribes to help doctors in the ER will increase efficiency and reduce physician burnout rate, but may increase error due to reliance on scribes to input information which may not be completely accurate. Often errors are caught when doctors do the documentation themselves (use of metacognition). How can we offset this issue of “error check”?
- Collecting secondary data from audit trails (unobtrusive and automated)
- Building support for data capture in real-world clinical environments. Standardized, but extensible and flexible infrastructure that can be used for data capture (e.g., generic templates that can be used in a mobile device)

The complexity and demands placed upon physicians within academic ED settings, characterized by team communication, contributes to error recovery as collective knowledge and expertise provides more opportunities for error detection to occur between physicians. Interruptions and multitasking not just compromise safety by increasing cognitive load, but also provide a source of error detection and correction through team work (learning through education and training). ISMMS’ team-based model of error detection and correction may outweigh the capacity for recovery of individuals when working alone, as observed at Mayo.

Importance of presenting information through data analytics and visualization to ER physicians.

- Our work has demonstrated a series of methods that can leverage these technologies to derive deeper insights into clinical workflow and associated issues and bottlenecks. The main advantage of data analytical techniques is the potential condensation of complex analyses into smaller nuggets of relevant quantifiable information about behavior and workflow that can be targeted to specific clinicians or groups of clinicians (i.e. nurses, physicians etc.).
- Visual analytics and visualizations can help reduce the burden and provide a series of techniques (as described in this report) that simplify the process of communicating results of workflow analysis to the target clinicians. It also allows informaticians to modify the presentation of the same set of results to different end-users. For example, summaries of analyzed workflow behavior can be presented in graphical ways to some physicians for quick perusal while including numeric content and more complex visualizations for administrators or researchers. This can help broaden the types of health care providers and administrators who can benefit from such visual analytics.

Mining EHR data logs for characterizing clinical and EHR workflows

- Data logs are products of user interactions with EHRs. They provide a simple and efficient mechanism to understand and characterize human interaction behaviors and EHR workflows. They are however challenging for data analysis as they require significant clean up and processing before they can be useful. Data logs can also be effective complementary to other sources of data. For example, we used data logs in combination with RFID to track both the physicians’ clinical workflow and their EHR workflow at the same time, providing valuable insights. Based on our series of studies that used EHR data logs independently and with RFID data, we found patterns of EHR use, evaluated ER efficiency metrics based on EHR usage, and clinical workflow activities of clinicians.

LIMITATIONS AND LESSONS

Our studies have a number of limitations. First, we studied two clinical environments with two different systems, with generalizability limitations, except for developed methodology. These studies need to be validated at other EDs and beyond. Second, we chose to focus on the attending physician mostly, as they are ultimately responsible for all decisions regarding the patient, although an attending physician’s workflow is also determined by other clinicians and the nature of the support provided by the team.

Third, this study was based on a small sample of physicians and a very large sample of patients at two different institutions. However, given that we computed EHR-based activities separately for each segment of the ED-based performance metrics, the potential associations are still valid. We did not capture the patient demographics or their clinical conditions for our analysis. Accounting for the differences in clinical conditions in the analysis could possibly weaken the associate effects that were observed.

Fourth, there are many challenges to conducting investigations in natural environment, where unanticipated events emerge, such as, overnight decision to change the use of technology (EHRs, sensor technology), brutally affecting our work, and so, the investigators have to be prepared to adapt to the situation by modifying the studies “on the run” without losing time. The PI has to be always prepared to adapt quickly and effectively and provide leadership role of the team

Finally, our research show that quantitative studies [data logs] are valuable in getting amount of time clinicians spent on various sections of EHR systems, but the context was missing. Qualitative studies provide that added value of not only contextualizing it [ethnography], but also interpreting the data with respect to clinician locations [RFID] in the ED, thereby providing a more composite picture of clinical workflow

LIST OF PUBLICATIONS: OUTPUTS

Journal Papers

- Kannampallil, TG, Abraham J, Patel VL. Methodological framework for evaluating clinical processes: A cognitive informatics perspective. *Journal of Biomedical Informatics*, Special issue on Cognitive Informatics Methods for Interactive Clinical Systems 2016;64, 342-351. PMID: 27847328
- Frisby J, Smith V, Traub S, et al. Contextual Computing: A Bluetooth-based Approach for Tracking Healthcare Providers in the Emergency Room. *Journal of Biomedical Informatics* 2017;65:97-104. PMID: 27913245
- Vankipuram A, Traub S, Patel VL. A method for the analysis and visualization of clinical workflow in dynamic environments. *Journal of Biomedical Informatics* Vol. 79, March 2018, Pages 20-31. PMID: 29410146
- Kannampallil TG, Denton CA, Shapiro JS, et al. Efficiency of Emergency Room Physicians: Insights from an Observational Study using EHR Log Files. *Applied Clinical Informatics* 2018; 9(1):99-104. PMID: 30184241
- Denton CA, Soni HC, Kannampallil TG, et al. Emergency Physicians' Perceived Influence of EHR Use on Clinical Workflow and Performance Metrics. *Applied Clinical Informatics*, 2018;9(03):725-733. PMID: 30208497
- Vankipuram A, Patel VL, Traub S, et al. Overlaying Multiple Sources of Data to Identify Bottlenecks in Clinical Workflow. *Journal of Biomedical Informatics*: X. 2019; 28:100004.
- Kannampallil TG, Denton CA, Shapiro JS, et al. A multi-scaled approach for characterizing physician and nurse activities using EHR logs and RFID tracking. *JAMIA Open* 2018 Dec. [Under review]

Book Chapters

- Vankipuram A, and Patel VL, Automated location tracking in clinical environments. A review of systems and impact on workflow analysis in the ER. In: Zheng K, Westbrook J, Kannampallil T, Patel VL, eds. *Cognitive Informatics. Reengineering Clinical Workflow for More Efficient and Safer Care*. UK: Springer; 2018: Chapter 13.

Conference Proceedings

- Patel VL, Kannampallil TG, Vankipuram A. Automated Monitoring of Clinical Workflows: Opportunities and Challenges. In: *Proceedings of International Symposium on Human Factors and Ergonomics in Healthcare*; 2016; San Diego, CA. Publishers; Human Factors and Ergonomics; 2016 July 27-31; San Diego, CA.
- Kannampallil TG, Zheng K, Patel VL. Analysis of Human Interactive Behavior for Improving Health IT Usability and Minimizing Patient Safety Risks. Presented as a tutorial at *AMIA Annual Symposium*; 2016; Nov 12-16, Chicago, IL.
- Kannampallil TG, Zheng K, Patel VL. Analysis of Human Interactive Behavior for Improving Health IT Usability and Minimizing Patient Safety Risks. *Instructional Workshop at AMIA Annual Symposium (AMIA)*; 2017 Nov 4-8; Washington, DC.
- Vankipuram A, Traub SJ, Patel VL. Clinical Workflow Visualization: Representation of Clinician Activity from Location Tracking Data. In: *Proceedings of the American Medical Informatics Association (AMIA) Annual Symposium*; 2017 Nov 4-8; Washington, DC. AMIA publishers; 2017.

- Patel VL. Innovative Methods based on R01 award supported by AHRQ. A Webinar presented to the Division of Health IT Team, AHRQ, 2018 March 21.
- Dymek C, Tai-Seale M, Patel VL, et al. Panel on EHR Log Data: An Untapped Health Data Goldmine for Clinical Informatics Research. In: Proceedings of the Annual Meeting of the American Medical Informatics Association (AMIA); 2018 Nov 3-7; SFO. AMIA publishers; 2018.

Tutorial/Instructional Workshop

- Kannampallil TG, Zheng K, Patel VL. Analysis of Human Interactive Behavior for Improving Health IT Usability and Minimizing Patient Safety Risks. Instructional Workshop at AMIA Annual Symposium (AMIA); 2018 Nov 3-7; San Francisco, CA.

Conference Abstracts (Posters)

- Denton CA, Nimo G, Shapiro J, et al. Perceived Effects of Meaningful Use Compliant Electronic Health Records on Clinical Workflow: A Preliminary Analysis. In: International Symposium on Human Factors and Ergonomics in Healthcare; 2016 July 27-31; San Diego, CA.
- Denton CA, Shapiro J, Nimo G, et al. Perceived Effects of Meaningful Use of Electronic Health Records on Clinical Workflow. In: Proceedings of the Annual Meeting of American Medical Informatics Association (AMIA); 2016 Nov 12-16; Chicago, IL.
- Soni HC, Denton CA, Serrichio A, et al. Clinicians' Perception of EHRs in Emergency Department Workflow. In: ASU BMI-Mayo Clinic Poster & Employer Networking Event, 2017 April 21; Mayo Clinic Campus, Scottsdale, AZ.
- Vankipuram A, Traub SJ, Patel VL. ClinicalWorkflow Visualization: Representation of Clinician Activity from Location Tracking and EHR log file Data. In: ASU BMI-Mayo Clinic Poster & Employer Networking Event, 2017 April 21; Mayo Clinic Campus, Scottsdale, AZ.
- Soni H, Vankipuram A, Denton CA, et al. Characterization of Clinical Workflow and Electronic Health Records in Emergency Medicine. In: Proceedings of Clinical Informatics Conference of American Medical Informatics Association, 2018 May 9; Scottsdale, AZ.

Seminars

- Patel VL. Sensor-based Monitoring of Clinical Workflows in Emergency Rooms: Opportunities and Challenges. Invited Speaker for Informatics Intervention Research Collaboration series presented by Columbia University's Department of Biomedical Informatics, 2016 June 21.
- Patel VL. Sensor-based Monitoring of Clinical Workflows in Emergency Rooms: Opportunities and Challenges. Invited Speaker for Center for Behavioral Cardiovascular Health series presented by Columbia University Medical Center, 2016 September 26.

Dissertation

- Vankipuram A. Utilization of Automated Location Tracking for Clinical Workflow Analytics and Visualization (Doctoral Dissertation: Advisor: Vimla, L Patel). Arizona State University; Nov. 2018. Parts of the work reported in this Dissertation was supported by Agency for Healthcare Research and Quality (AHRQ) through our collaborating site, located at Mayo Clinic, Phoenix, AZ.

Manuscripts in Progress

- Patel VL, Denton CA, Soni HC, et al. Electronic Health Record System and its Impact on Emergency Department Clinical Workflow in Academic and Non-Academic Hospital Environments. [J Patient safety]
- Patel VL, Kannampallil T.G., Vankipuram A., et al. Nature of the Beast: Recommendations for Efficient EHRs with Low Safety Risks in Emergency Care [BMC Medical Informatics and Decision Making]

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